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# Hybridized Conceptual Model of Artificial Intelligence Capability

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**Abstract**

***Background***: *Hybridization is the process of integrating two or more models together to have a robust model. Artificial intelligence capability is the ability of a firm to select, organize and use its AI specific resources. In other to study the impact of AI capability on organizational creativity, studies proposed the idea of framework of AI capability model, it's concept that investigated the effect of AI capability on organizational creativity and it performance. However, some essential factors that are necessary and relevant in enhancing the effect of AI capability in business organization are inadequate, despite the revolutionary potential that AI capabilities may promote, hence, this study bridge the gap.* ***Aim:*** *This study is based on resource base theory of the firm in the business domain that explored the impact of a hybridized model of Artificial Intelligence capability on organizational success.* ***Method:*** *The study integrated and enhanced two AI capability model by hybridization and addition of more factors, thus thirteen (13) factors were added. They were classified into external, instantaneous and temporal factors. The external factors are the input factors to the model, they are the independent variables, the instantaneous otherwise known as the mediating factors are time bounded factors with no delay while the temporal factors are the dependent variables, and they are also time-bounded factors with delay. The identified factors were based on theories and other related literatures. Nodes was used to represent the factors and the casual relationship of the identified factors was represented in form of flow arrows to show its connectivity. This was how the conceptual model was derived.* ***Results****: The inclusion of the thirteen factors resulted in a robust conceptual model, used to influence important decisions in business organizations.*

**Keywords:** *Hybridization, Artificial Intelligence capability, Knowledge Sharing, Collaboration, Organization success*

## 1. Introduction

Hybridization can be defined as the process of integrating two or more models together in order to have a robust model. Building on the resource base theory of the firm in the business domain and review of relevant literatures, it shows that there is an existing model on Artificial intelligence (AI) capability, called conceptual research model (Mikalef & Gupta, 2021) and AI capability Model (li, et al., 2022). However, more AI capability factors are needed in order to bring about an overall organization success, which the current study aims to solve. In this study, an enhanced AI capability model by hybridization was obtained by addition of more factors, to create a robust model.

The study integrated and enhanced the two models by hybridization and addition of more AI capability factors that can be used by business owners and employees for quick and accurate decision which is necessary for the success

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of an organization in the business domain. These factors were gotten from the review of relevant literatures and the resource base theory of the firm.

Artificial intelligence is widely recognized as the next source of business value, a key technology guiding a new wave of technological innovation and industrial transformation (Li, Yan, Yang & Gu 2022), as a result, AI technology is now becoming increasingly important (Townsend et al., 2018), many companies are now embracing new technologies aimed at achieving high performance and competitive advantage (Wamba-Taguimdje et al, 2017). Among these technologies, AI has occupied a prominent position and has attracted attention from both the literature and business organizations. According to Davenport (2018), AI might be the technology force with the greatest disruptive potential currently in use, similarly, a study by Brynjolfsson and Mcafee (2017), also shows that AI is the most important general-purpose technology of our era, particularly with regards to machine learning techniques. The goal of AI is to make computers capable of carrying out tasks that would typically need human intelligence as a result, AI will eventually replace many human-held jobs (Jerrahi, 2018).

Artificial intelligence is also very much useful in knowledge management and in all fields of human endeavor, helpful in the learning and business environment. Zheng et al. (2021), asserts that mere adoption of AI tools without appropriate knowledge management processes (KMPs) is not effective. It is essential to note that knowledge management (KM) is a key tool for firms to gain a sustainable competitive advantage. Individual knowledge and knowledge sharing are the main areas of knowledge management for organizational achievement in the information age. The development of AI technology promises several benefits in organizations, which will bring about business value (Enholm et al; 2021). In order for businesses to achieve strategic goals, knowledge sharing is essential since it brings about collaboration and create new sources of knowledge, update problem-solving abilities, and become more aware of how other people make decisions (Li et al; 2022).

Although AI have attracted the attention of business organizations in the last decade due to advancement in machine learning, organizations are still struggling to integrate AI into their businesses because they don't understand how to use it strategically (Borges et al., 2020), effective knowledge management will be facilitated by the incorporation of AI techniques into knowledge organizations, which will result in the transformation of individual knowledge into organizational knowledge (Liebowitz, 2001). Knowledge workers in business organizations need to have creative skills and adapt the use of AI in their business in other to bring about creative, innovative, and useful solutions thereby creating an edge in the business world (Botega & da Silva, 2020).

One of the key drivers of this progress is the identification of AI capability factors, needed to bring about organization creativity, performance and success.

## 2. Related Works

### 2.1. Resource Base Theory.

The Resource base theory (RBT), is a management framework that emphasizes a firm's internal resources as sources of sustainable competitive advantage, it suggests that a firm's internal factor such as resources and capabilities, can lead to superior performance when effectively used (Porter, 1989). Resource base theory (RBT) begins by supposing that firms are bundles of resources and capabilities (Barney, David, Ketchen & Wright, 2011). The RBT of the firm has become one of the most widely applied theoretical perspectives in explaining how the resources that an organization has under its control can lead to differences in performance in the same industry (Barney, 2001). That apart from the technology itself, other human and complementary organizational resources are required to utilize its investments (Gupta & George, 2016; Mikalef, Pappas, Krogstie, & Giannakos, 2018).

These, and other previous research consistently show how effective the RBT is, in explaining the connection between organizational resources and firm performance. Since the aim of this study is to identify the necessary AI capability factors and enhance the existing AI capability model that will enable business owners make quick and accurate decision which will result in business gains, the RBT was a suitable choice to serve as the study's underlying theoretical framework.

### 2.2.1 Approaches in Resource Base Theory

**VRIO framework (Valuable, Rare, Inimitable, organization)** the VRIO framework, proposed by Jay Barney in 1991, is a business framework that forms part of a firm's larger strategic scheme, is a strategic analysis tool used to assess the competitive advantage of a firm's resources and capabilities. The VRIO model proposes the new criteria of the organizational embeddedness of a resource (Utami & Alamanos, 2023).

**Dynamic Capabilities**: a concept in strategic management that describes a firm's ability to adapt and innovate in response to changing environments. Dynamic capabilities emphasizes the importance of a firm's ability to adapt, integrate and change its resource base over time. It is also the capacity to systematically solve problems, enabled by its tendency to sense opportunities and threats, to make prompt decisions and to effectively implement strategic decisions (Ferreira, Coelho & Mountinho 2020).

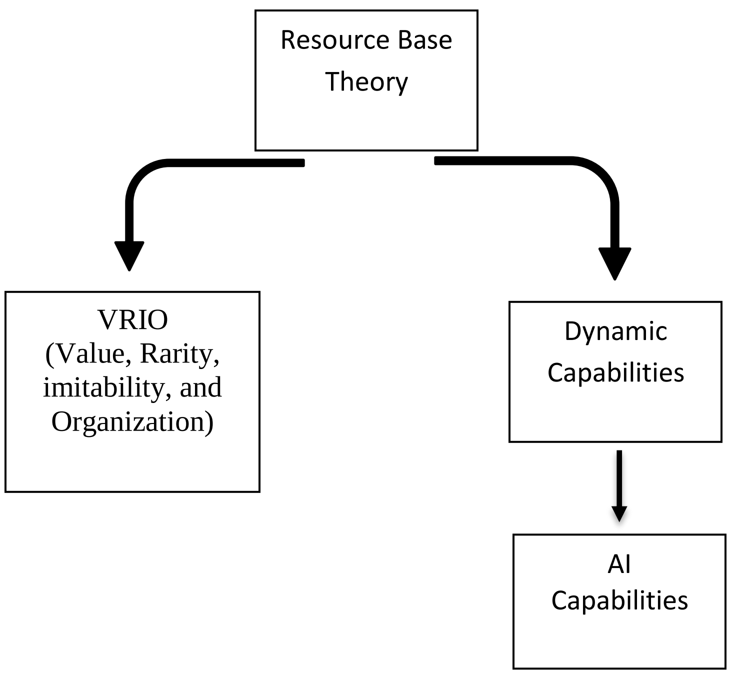


Figure 2.1**.** Approaches in Resource Base Theory (Source: Adapted from Tigunt and Hossari (2020)).

AI capabilities are often associated with the "***Dynamic Capability***" approach (Tigunt & Hossari, 2020).
Dynamic capabilities refer to an organization's ability to adapt, evolve, and innovate in response to changing market conditions and technological advancements.

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Therefore, this study is built based on the dynamic capability approach, which describes the ability of a firm to adapt, evolve, and innovate in response to changing market conditions and technological advancements (Teece, 2022). In addition, it will enhance organization's ability to deal appropriately with rapidly changing environment (Felsberger et al., 2022).

## 2.1 Conceptual Research Model of AI Capability

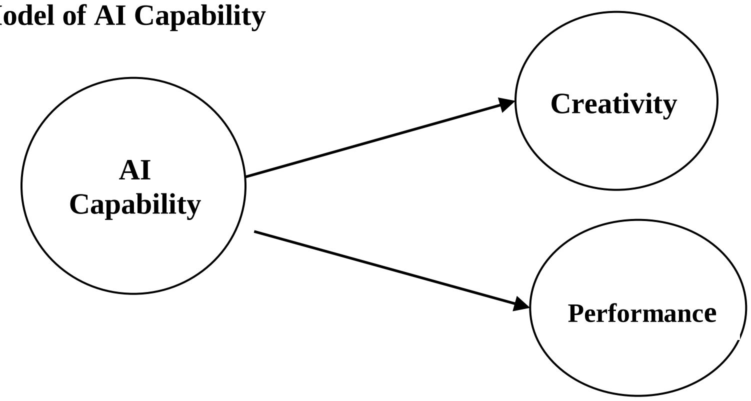


Figure 2.2. Conceptual Research Model (Source: Adopted from Mikalef and Gupta (2021)).

Grounded on the resource base theory of the firm, Mikalef and Gupta (2021), put forward a conceptual research model that seeks to examine the resources that are required to build an AI capability.
Empirical result from the study shows that AI has a positive effect on organization creativity and performance.

### *2.1.1 Factors of conceptual Research Model*

The conceptual research model by Mikalef and Gupta (2021), is a model of the resource base theory. The model has a total of three (3) factors, ranging from AI capability to Organizational performance. Based on the diagram in figure 2.2. The factors are classified into two, namely, the external and temporal factors, shown in table 2.1

Table 2.1. Factors of Conceptual Research Model

| External | Temporal |
|---|---|
| 1. AI capability | 1. Organizational performance |
| | 2. Organizational creativity. |

## 2.2 AI capability Model

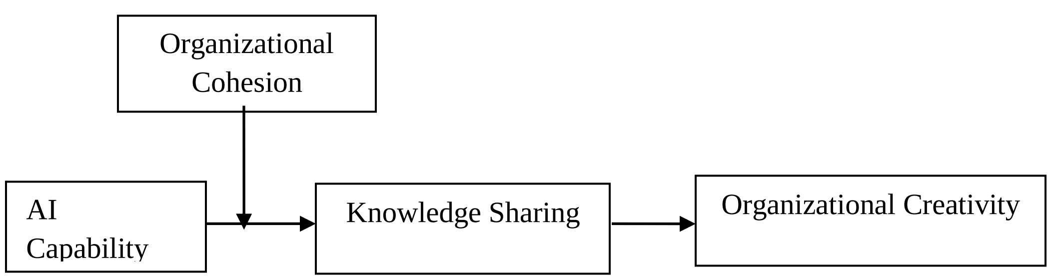


Figure 2.4. AI Capability model (Source: Adapted from Li et al. (2022)).

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AI capability model is a model put forward by Li et.al (2022), th**ey** presented an AI capability model, and also introduced the concept of AI capability, examined the influence path between AI capability and organizational creativity from the perspective of knowledge sharing and the effect of organization cohesion and how it helps in promoting AI capability, empirical result shows that AI capability has a positive impact on knowledge sharing, knowledge sharing has a positive impact on organizational creativity and knowledge sharing mediates the relationship between AI capability and organizational creativity.
The model has a total of (4) factors based on the diagram in figure 2.4.
The factors are classified into three namely, the external, instantaneous and temporal factors, shown in table 2.2

Table 2.2. Factors of AI Capability Model

| External | Instantaneous | Temporal |
|---|---|---|
| 1. AI Capability | 1. Organization Cohesion<br>2. Knowledge sharing | Organizational Creativity |

Based on the factors stated in table 2.1 and 2.2 respectively, there is a need for a comprehensive AI capability model that has detailed AI capability factors for organization success. Such as, data, technology, basic resources, technical skills, Business skills, Interdepartmental coordination, Organizational Change Capacity, Risk Proclivity, Tangible Resources, Human Resources, Intangible Resources, Organizational Success (Li et al., 2022, Mikalef & Gupta 2022, Chowdury 2022, Husan & Pinky, 2023).

## 2.3. Integrated Artificial Intelligence Capability Model

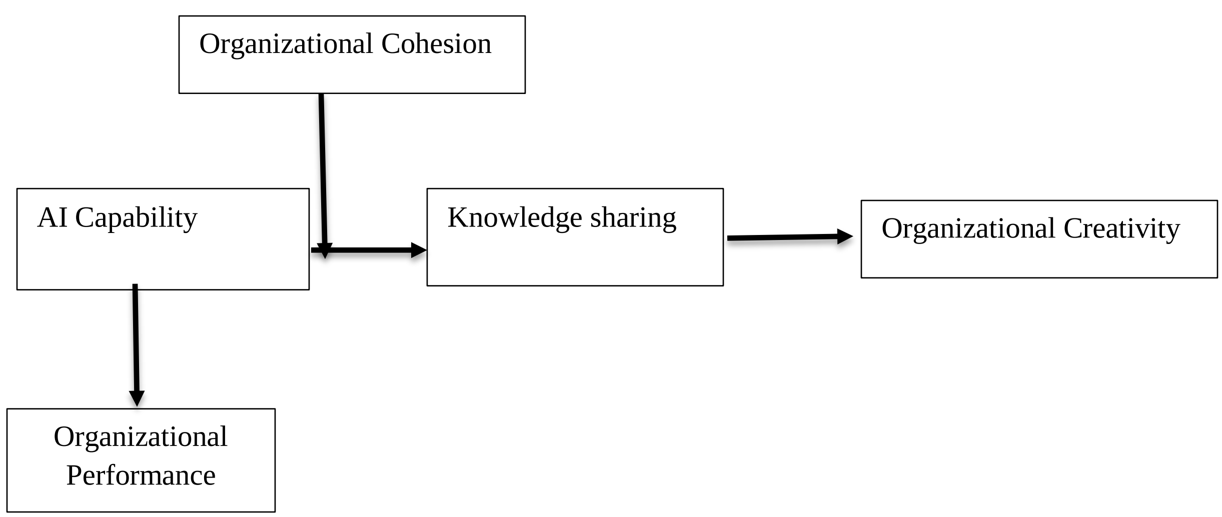


Figure 2.8**.** Integrated Model of AI capability (Source: Adapted from (Li et al, 2022; Mikalef and Gupta, 2021).

Figure 2.8 shows the existing AI capability model and conceptual research model for organizational creativity and performance by Li et al (2022) and Mikalef and Gupta (2021)
From figure 2.8, the integrated model has seven factors. Three (3) from the conceptual research model of Mikalef and Gupta (2021) and four (4) from AI capability model by Li et al (2022), with the intersection of AI capability

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and organizational creativity in the two model. It has a total of one (1) external factor, two (2) instantaneous factors and two (2) temporal factors as shown in table 2.3.

Table 2.3. Factors of Integrated Research Model

| External Factor | Instantaneous Factor | Temporal Factor |
|---|---|---|
| • AI capability | • Organizational Cohesion<br>• Organizational Creativity | • Organizational creativity<br>• Organizational performance |

From figure 2.8 and table 2.6, the external factor of the model is One (1), AI capability, two (2) instantaneous factors namely organizational cohesion and organizational creativity and two (2) temporal factors organizational creativity and organizational performance.
However, based on the factors identified in this study, theirs' a need for an inclusion of more factors relevant for organization success, the present study comes up with an addition of thirteen (13) factors in other to enhance the model.

Table 2.4. Integration of AI model factors and the proposed enhanced model factors

| Conceptual Research Model (Mikalef & Gupta, 2021) | Proposed Enhanced Hybrid Model of AI Capability |
|---|---|
| • AI capability<br>• Organizational creativity<br>• Organizational Performance<br>**AI Capability Model (Li et al., 2022)**<br>• AI capability<br>• Knowledge Sharing<br>• Organizational Cohesion<br>• Organizational Creativity | • Data<br>• Technology<br>• Basic Resources<br>• Technical Skills<br>• Business Skills<br>• Inter departmental Coordination<br>• Organizational change Capacity<br>• Risk Proclivity<br>• Tangible Resources<br>• Intangible Resources<br>• Human Resources<br>• Collaboration<br>• Organization success. |

Table 2.4 shows the integration model factors and the factors of proposed enhanced hybridized model of AI capability.

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Table 2.5. Summary of External Factors of the Hybridized conceptual Model of Artificial Intelligence Capability based on the Resource Based Theory of the Firm

| Factors | Symbol | Definition | References |
|---|---|---|---|
| Data | $D_t$ | These are facts, information, or pieces of knowledge that are collected, stored and analyzed used to make informed decision in other to gain competitive advantage. | Parkins, (2017), Ransbotham et al, (2018). |
| Technology | $T_n$ | This refers to the infrastructure and equipment necessary for the adoption and implementation of AI within organizations, encompassing all equipment for fast data analysis and execution of complex algorithms, such as GPU-intensive clusters and parallel computing techniques | Mikalef and Gupta (2021), Chui and Malhotra (2018) |
| Basic Resources | $B_r$ | Emphasizes essential commodities required for organizations to establish AI capabilities. | Mikalef and Gupta (2021), Gupta and George, (2016), Davenport and Ronanki (2018). |
| Tangible Resources | $T_r$ | Tangible resources refer to physical assets that can be bought, sold, or quantified in monetary terms. This includes financial assets such as cash, investments, and securities, as well as physical assets like property, equipment, and inventory. | Mikalef and Gupta (2021), Barney, (1991). |
| Technical Skills | $T_s$ | The ability to develop, implement, and manage AI algorithms, as well as to ensure that AI applications align with organizational goals. | Mikalef and Gupta (2021), Wilson, Daugherty and Bianzino (2017). |
| Business Skills | $B_s$ | Skills needed by managers and employees for a successful implementation and utilization of AI technologies within organization. | Mikalef and Gupta (2021), Davenport and Ronanki (2018). |
| Interdepartmental coordination | $I_c$ | Collaborative efforts and shared values among different departments within an organization. It is also a state characterized by high levels of shared values, mutual goal commitments, and collaborative behaviors. | Mikalef and Gupta (2021), Ransbotham et al. (2018). Souder (1977) |

| | | | |
|---|---|---|---|
| Organizational-change capacity | $O_y$ | Refers to an organization's ability to successfully transition from old processes to new ones, particularly in the context of adopting artificial intelligence (AI) technologies. | Mikalef and Gupta (2021), |
| Risk Proclivity | $R_p$ | An organization's inclination towards embracing risk in pursuing new ventures, such as adopting artificial intelligence (AI) technologies. | Mikalef and Gupta (2021), Ransbotham et al. (2018). |
| Human Resources | $H_r$ | Refers to both technical expertise related to AI technologies and business acumen necessary for effectively integrating AI into operations. | Mikalef and Gupta (2021), Bharadwaj, (2000), Ravichandran and Lertwongsatien, (2005). |
| Intangible Resources | $I_r$ | Resources considered more challenging for competitors to replicate. | Mikalef and Gupta (2021), Grant (1991). |

**Instantaneous hybridized conceptual Model of Artificial Intelligence Capability based on the Resource Based Theory of the Firm**

Three (3) instantaneous factors of the hybridized model was identified namely: AI capability, Knowledge Sharing, and Collaboration.

Table 2.6. Summary of Instantaneous factor of the Hybridized conceptual Model of Artificial Intelligence Capability based on the Resource Based Theory of the Firm

| **Factor** | **Symbol** | **Definition** | **References** |
|---|---|---|---|
| AI Capability | $A_c$ | It emphasizes a company's ability to effectively select, organize and utilize resources specifically tailored for AI applications. | Mikalef and Gupta (2021), Li et al., (2022). |
| Knowledge Sharing | $K_s$ | It involves the process of generating, utilizing and disseminating organization's information and also, the sharing of employee's skills, experience and knowledge within an organization. | Leoni, et al., (2022), Li et al., (2022), Bencsik (2021). |

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|---|---|---|---|
| Collaboration | $C_n$ | Involves stakeholders working together and utilizing data to achieve common goals through shared activities | Hong et al (2019), Khatib,et al.(2022), Fresdstorm et al. (2022). |

**Temporal Factors of the Hybridized conceptual Model of Artificial Intelligence Capability based on the Resource Based Theory of the Firm**

Four (4), temporal factors were identified in the model based on literatures and RBT namely: Organization Performance, Organization Creativity, Organization Cohesion and Organization Success.

Table 2.7. Summary of Temporal factor of the Enhanced Hybrid Model of Artificial Intelligence capability Model

| Factor | Symbol | Definition | References |
|---|---|---|---|
| Organization Cohesion | $O_n$ | It is the degree of unity within a group, essential for the formation and sustainability of groups within an organization. | Li et al., (2022), Forsyth (2021). |
| Organization Creativity | $O_c$ | It involves leveraging AI to foster innovative ideas within an organization. | Botega and Silva (2021), Machado, Mgrelli and Dwivedi (2022). |
| Organization Performance | $O_p$ | Describes how a firms use of AI can enhance performance | Wamba-Taguindje and Wamba et al; (2020), Mishra, Ewing and Cooper (2022). |
| Organization Success | $O_s$ | The achievement of goals that aligns with an organization's mission. | Ain et al. (2019), Johnk et al. (2020). |

From table 2.4, 2.5 and2.6, the factors identified were based on scholarly literatures and the Resource based theory of the firm. Which is one of the major contribution of this study to the body of knowledge.

## 3. Methodology

In this session, a framework underlying the design structure of the study is given. The framework implemented is adapted from Mustapha (2019) and Mustapha et al. (2020). As a result of the complex and dynamic nature of the business environment, this methodology is applicable for formal specification and representation. This research methodology serves as a guide to develop and evaluate the AI Capability model grouped into two (2) stages, (Domain and Design) used as a basis for the model construction. Factors identified were categorized into three namely: External, Instantaneous and Temporal factors. The causal relationship of the identified factors of the AI capability model (Li et al., 2022) and conceptual research model (Mikalef & Gupta 2021) were based on the Resource base theory (RBT) of the firm. For the identification of these factors, the internet and library resource were used to review relevant literatures from experts in various domains, especially in the domain of AI

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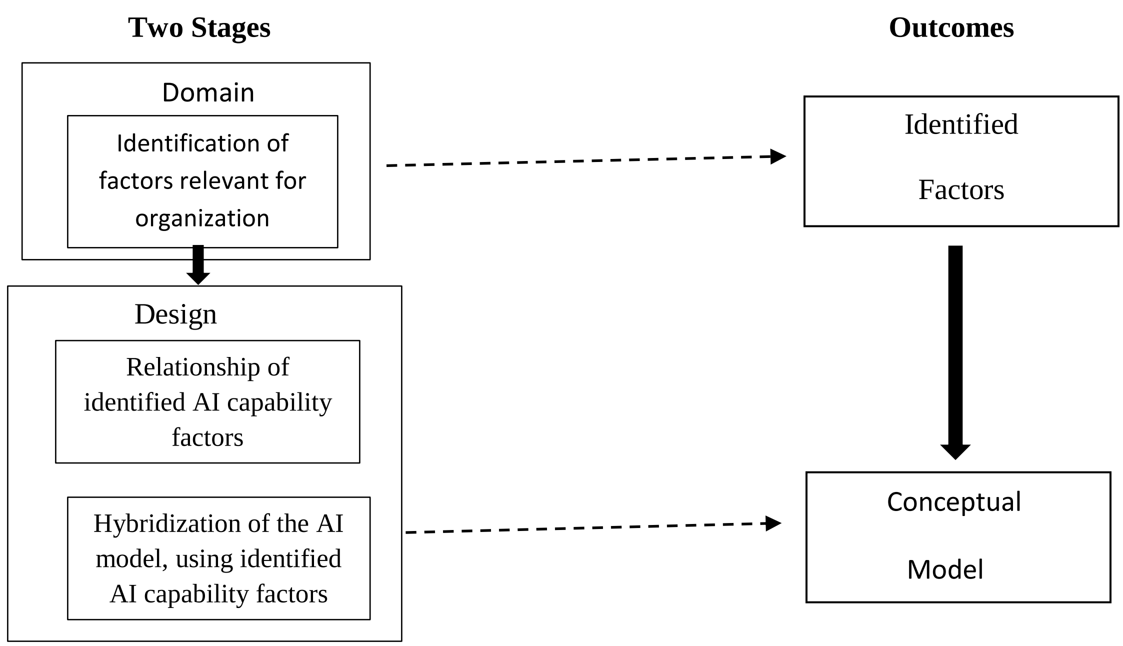


Figure 3.1. Research Methodology (Source: Adapted from: Mustapha, 2019; Mustapha et al. (2020)).

## 3.1. **Domain model stage.**

In this stage, the factors relevant for organizational success are identified. The stated model has eighteen (18) factors as against the five factors identified by Li et al. (2022), AI capability model and three identified by Mikalef and Gupta in their conceptual research model for AI capability. The eighteen (18) factors identified were categorized into three namely: external, instantaneous and temporal factors. The causal relationship of the identified factors of the AI capability model (Li et al., 2022) and conceptual research model (Mikalef & Gupta 2021) were based on the Resource base theory (RBT) of the firm.
For the identification of these factors, the internet and library resource was used.

## 3.1. Design model stage

In the design model stage, thirteen (13) AI capability factors such as data, technology, basic resources, technical skills, business skills, interdepartmental coordination, organizational change capacity, Risk proclivity, Tangible resources, Intangible Resources, Human Resources, collaboration, and organizational success were obtained by the expansion and addition of more factors from other related literatures, combined to enhance the AI capability model, each of the factors in the model is represented by a node, and the casual relationships between the factors are shown using flow arrows. To create a model of enhanced AI capabilities, the direct and indirect relationships were taken into account based on the theories of each concept. The model's variables were divided into external, instantaneous, and temporal factors.

The external factors are set of input factors to the model, while the instantaneous or moderating factors are factors whose process occur instantly. The temporal factors, are time-bounded factors usually the dependent

variables, they depend on the external and instantaneous factors and whose processes occur with many delays in time.

The design model represents the relationship between factors identified from the domain model stage. For example, to demonstrate the stage, if A, B, C, D, and E are factors identified from the domain model stage, then the design model can be presented in figure 3.4. if A, B, C, D and E are factors identified from the domain model stage,

the relationship between these five factors (A, B, C, D and E) is shown using a set of flow arrows as shown in figure 3.4 obtained based on theories where the factors are identified.

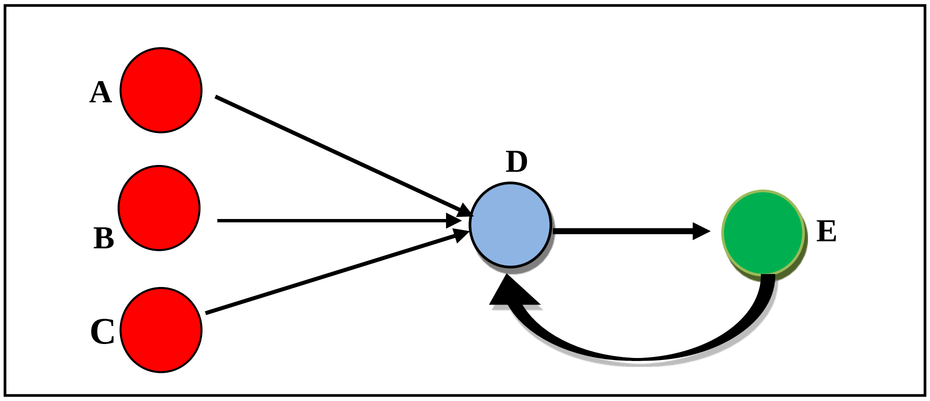


Figure 3.4. Example of Design Model

From figure 3.4, A, B, C are input factors, D is an instantaneous factor while E the temporal factor, determined by the combination of the input (external) and instantaneous (mediating) factor.

## 4. Result and Discussions

### 4.1. Identification of AI capability Model Factors

In enhancing the integrated AI capability model, factors relevant for organization success were identified based on theories of the RBT and scholarly literatures on AI capability. The factors identified include Data, Technology, Basic Resources, Technical Skill, and Business Skills, Interdepartmental coordination, Organizational change capacity, Risk Proclivity, Tangible Resources, Intangible resources, Human Resources, Collaboration and organizational success.
Hence, details on how the factors were identified in our present study and the casual relationship based on literatures are as follows.

**Data***:*

Although businesses have historically used structured data to help them make decisions, data itself is often referred to be the "new oil" and, when purified, can be a source of competitive advantage (Parkins, 2017). According to (Ransbotham et al., 2018), managers view data as one of the major facilitators for maximizing the AI potential. Today's organizations have captured a large diversity of data stemming from multiple sources and in

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different formats (Kersting & Meyer, 2018). In fact, as high-quality data is utilized to train AI algorithms, its availability is seen to be crucial.

Ransbotham et al. (2018), found that organizations who integrates AI in their business follow a common understanding within their management teams which regards data as a corporate asset. One of the significant breakthroughs is the convergence of big data with AI which determines how firms drive business value from their data resources (Bean, 2017). When it comes to developing AI applications that can deliver value, the quality of the data that are fed into such algorithms are of great importance. There is a great demand on good quality data, since AI systems require massive training data-sets, and applications effectively "learn" from available information in a manner similar to the way humans do.

According to Zhao, Fan, and Hu, (2014), organizations have access to two types of data namely: internal and external data. Internal data include all that are created by the organization's internal operations such as accounting, sales, human resource management, and manufacturing/production. Historically, internal data make up a sizable fraction of the total data that organizations use to make decision. Yet, relying on such data to base business decisions on is unlikely to result in a competitive edge (Mikalef & Gupta, 2021). External data are those that are not directly related to the company's activities, but can offer new and insightful information about the competitive environment in which modern firms operate. Thus, firms interested in leveraging data to enable AI must integrate internal and external data sources, while at the same time manage to cleanse, process, and distribute data throughout organizational boundaries as needed.

**Technology:**

According to Chui and Malhotra (2018), lack of technological infrastructure is one of the main barriers in adopting AI in organizations. As infrastructure investments are needed at numerous levels for AI technology, this presents a significant barrier for many organizations. The amount of data that needs to be stored for AI applications varies greatly depending on the application and the source material, as well as the stage of application development and use. As a result, businesses must invest in storage infrastructures that can handle the volume and various formats as well as be scalable depending on demand (Bayless et al., 2020).

Aside from flexible data storage, AI technologies also put pressure on businesses to spend money on equipment that can analyze data fast, and execute complicated algorithms. Common approaches include the use of GPU-intensive clusters and using parallel computing techniques to deal with the processing power required (Nurvitadhi et al., 2017). As a result of the high cost of AI infrastructure, many businesses are also using cloud-based solutions, and in recent years, a new market for integrated cloud services that enable the use of sophisticated AI techniques through simple API calls has grown significantly (Del Sole, 2018).

As AI technologies require infrastructure investments at multiple levels, this proves to be a major setback for many organizations, particularly those with less slack resources (Dwivedi et al., 2019). For instance, deep learning systems need to be fed current data constantly since they can retrain themselves as they work. This essentially means that infrastructure improvements will be made along the entire pipeline, from data ingest to inference, storage to transport across high bandwidth networks, and computing power. The sort of procedures utilized also has a significant impact on the technological infrastructure, thus businesses may find themselves needing to invest in a number of different supporting technologies in other to boast performance.

**Basic resources:**

Organizations must be able to commit the time and money necessary for AI projects to succeed, investments and time are a group of basic resources which are required to create an AI capability**.** In addition to the expenditures in data and the technological infrastructure needed to support AI (Mikalef & Gupta, 2021). Most efforts will need some time to mature before being deployed and providing value because the bulk of enterprises are only now experimenting with AI (Ransbotham et al., 2018).

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According to Davenport and Ronanki (2018), the experimentation with proof-of-concept pilots is regarded as a best practice when it comes to AI initiatives, where the organization can test different technologies and methods. Giving AI applications enough financial resources to grow is another crucial area in which businesses must invest in (Mikalef & Gupta, 2021) however, allocating financial resources for AI projects is crucial because internal budgeting for such efforts calls for technical and non-technical staff to be able to use some of their working hours in building AI applications and to have the required technological infrastructure necessary for the success of an organization.

**Tangible resources:**

According to the RBT literature, marketable resources are those that can be bought or sold (Barney, 1991). For instance, there are various categories of tangible resources, such as financial assets and physical assets like debt and equity. As tangible resources are largely accessible to all businesses in the market, they are unlikely to offer a distinct competitive edge. However, while tangible resources are required, they are not sufficient to build capabilities (Mikalef & Gupta, 2021) but necessary for the promotion of wealth, provide the foundation for operational efficiency and contribute to overall competitiveness.

**Technical skills:**

According to Mikalef and Gupta, (2021), technical AI skills, are skills necessary in order to deal with the implementation and realization of AI algorithms, managing the infrastructure to support such initiatives, as well as those to introduce and ensure AI applications adhere to goals. According to Spector and Ma (2019), algorithm developers are required to use the most recent AI research and turn it into repeatable procedures using mathematical formulas that can be implemented through hardware and software. MIT Sloan Management review, three key roles that will emerge as technical profiles in the age of AI are: Trainers, trainers are concerned with teaching AI systems how they should perform, and include tasks of helping service chat bots, for instance, identify the complexities and subtleties of human communication. Explaining the inner workings of AI systems to non-technical audiences, explainers help close the gap between technologists and business managers. Sustainers: According to Wilson, Daugherty and Bianzino (2017), sustainers make sure AI systems are functioning as planned and that any unexpected repercussions are dealt with effectively. A list of more specific work duties that are already essential for modern businesses is provided for each of these three roles. It is believed that those with this talents will become a commodity across firms.

**Business skills**:

One of the most frequently mentioned obstacles to implementing and using AI technologies in an organizational setting is managers' lack of understanding of how and where to employ such technology (Fountaine et al., 2019). It takes actual knowledge and commitment on the side of the leaders to create a significant transformation in order to realize the business value of AI investments. Additionally, managers must be aware of the possible applications of AI as well as how to manage the shift to AI-enabled tasks. One-third of managers, according to Davenport and Ronanki (2018), are unaware of how AI technologies operate. Therefore, it is crucial that managers get familiar with the various AI technologies and their possible applications across various organizational roles.

The capability of managers to launch and organize AI installations is another crucial factor (Kolbjrnsrud, Amico, & Thomas, 2016). This is particularly important when considering the strong forces that exist within organizations against change, and the threat that AI may replace many of the jobs that are currently held by employees. Thus, to reduce frictions and potential sources of inertia that can delay the adoption of AI and restrict commercial value, managers must foster positive working relationships between technical staff and personnel of the line function (Kiron, 2017). It will probably be challenging for other businesses to replicate the ability to take

advantage of the potential presented by various AI technologies and to manage the organizational change that goes along with AI deployments.

**Human resources**:

An organization's human capital is frequently evaluated by evaluating the knowledge, skills, experience, leadership traits, vision, communication and cooperation capabilities, and problem-solving abilities of its staff (Mikalef & Gupta, 2021). According to earlier studies on digital capabilities, technical and business skills are essential components of human capital (Bharadwaj, 2000; Ravichandran & Lertwongsatien, 2005). A firm's human AI resources should include both technical and business talents unique to artificial intelligence, as human resource is crucial for optimizing organizational goals.

**Intangible resources:**

Intangible resources are those that are thought to be more challenging for other companies to replicate and are of particular significance in uncertain and volatile markets (Morgan, Vorhies, & Schlegelmilch, 2006). These three main types of organizational resources were identified in the RBT (Grant, 1991) as the three main types of organizational resources. When compared to the other two types of resources, intangibles are significantly more elusive and challenging to locate within firms (Grant, 1999). They fall under the category of resources that match the RBT's VRIN classification (Seddon, 2014). Intangible resources' variability and lack of duplicability are due to the fact that they are created through a special mixture of organizational history, people, process and conditions (Mikalef &Gupta, 2021).

**Inter-departmental coordination:**

Souder (1977), define interdepartmental coordination as "a state of high degrees of shared values, mutual goal commitments, and collaborative behaviors". Recent studies in AI and business value contend that in order to unleash the value of AI technologies, organizations must foster a culture of teamwork, collective goals, and shared resources (Ransbotham et al., 2018). This is in line with the long-standing observation that inter-departmental coordination plays a key role in enabling innovation and creativity in organizations (Evanschitzky, Eisend, Calantone, & Jiang, 2012). According to Fountaine et al. (2019), the most effective AI is produced by cross-functional teams with a range of specialties. By doing this, business may ensure that AI projects consider their entire organizational priorities in addition to particular business issues. As a shared language and a common understanding of employees between different departments will lead to reduced times in deploying new AI applications or adapting existing ones, it is possible that improving interdepartmental coordination will make organizations more agile and adaptable in deploying AI applications (Mikalef & Gupta, 2021).

**Risk proclivity:**

Ransbotham et al. (2018) discovered that firms that embrace a more risk-oriented strategy to new ventures like AI reap the rewards considerably before their competitors or new entrants do in their recent survey of top-level executives in 29 industries and situated in 126 countries that take on risk increase their dedication to AI and, in doing so, solidify their position, making it more difficult for others to catch up.

According to Ransbotham et al. (2018), artificial intelligence (AI) is one of the most exciting, competitive, and value-added aspects of business in the future. This finding suggests that risk-takers view AI as an opportunity they must seize before rivals do. Fountaine et al. (2019), who contend that firms must move away from risk-averse strategic orientation and become flexible, exploratory, and adaptable, also stress the change in attitude necessary to get benefit from AI. The fundamental tenet is that businesses that are open to departing from established norms and embracing novel, ambitious goals are also more likely to witness the development of robust AI capabilities than those that take a more cautious approach. Based on the aforementioned, it is safe to say that

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businesses with a strong inclination for risky endeavors will probably adopt AI first and benefit from the first-mover advantage.

**Organizational change capacity**:

Focuses on the potential issues that may result from failing to switch from an old process to a new one (Mikalef & Gupta, 2021). AI applications introduce significant changes to how organizations perform their key activities, either by replacing traditionally human-executed tasks, or by augmenting existing processes (Zheng et al., 2017). According to Ransbotham et al. (2018), planning for and managing such change at different organizational levels is crucial to getting the most out of AI investments.

It is crucial that managers cultivate the ability to predict, organize, and carry out change at an organizational level because each business will present a distinct combination of inhibiting variables that delay or even block change. The most significant hurdle to exploiting AI investments, according to a recent Appian poll of 500 high level IT managers (Appian, 2019), was altering the current business and IT cultures. Even with vast amounts of data, highly qualified technical personnel, and cutting-edge AI infrastructure, an organization that is unable to leverage these and transform its current way of doing business is unlikely to be able to benefit from AI investment.

**Collaboration:**

Hong et al (2019), defined collaboration as the working together and use of data by stakeholders to achieve common goals by engaging in shared activities.

Khatib, Kherbash, Aiqassimi and Almheiri (2022), in their study, investigates the applicability of collaborative environment and how organization establish their regulatory policies to ensure effective adoption of tool, generate operational excellence and stakeholder satisfaction. Findings from their study reveal how participants saw a clear value in collaborative environment and systems that drive operational excellence.

Fresdstorm et al. (2022), states how collaboration attracts positive sentiments, and it effect on performance depend on communication which enhances innovation by bringing diverse perspectives and skills together. Effective collaboration improves efficiency, to gain business value, collaboration among employee is an essential factor.

**Organizational success**:

This is effectively reaching goals, geared towards organization's mission.

Ain et al. (2019), presented a comprehensive knowledge on the adoption and utilization of business intelligence tools for success. An effective AI adoption in organization will leverage business value, geared towards organization success, with effective leadership success factors (Hussan & Pinky 2023), managers need to embrace how AI drives changes at the task, process and business model level in diverse application areas that offers a competitive advantage to organizations (Brynjolfsson & MacAfee 2017).

In the proposed enhanced hybrid model of AI capability, these thirteen (13) factors identified were categorized into three (3) different groups namely; the external, instantaneous and Temporal Factors. The external factors serve as inputs and independent variables to the model, while the instantaneous and temporal factors are dependent variables. The two are time bounded factors but for the instantaneous factors, the process is instant, contrary to the temporal factor where the process involves more delay. The casual relationships among the categories of the factors are represented symbolically in form of nodes and flow arrows to form a conceptual model.

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### 4.3. Hybridized Conceptual Model of Artificial Intelligence Capability

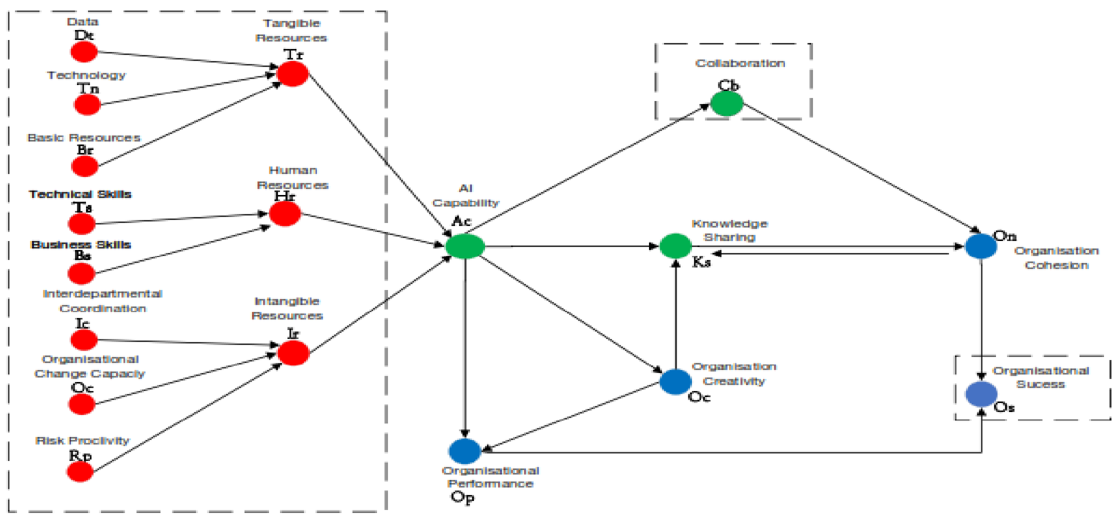


Figure 4.1. Proposed Hybridized Conceptual Model of AI Capability

## 5. Conclusion

This study presented a hybridized model of Artificial Intelligence capability in the business domain that can assist managers, business owners in making quick and accurate decisions. The study hybridized and enhanced an AI capability model by integrating two existing AI capability model and addition of more factors to have a comprehensive Conceptual model. the study presented a total of eighteen (18) AI capability factors, five (5), from previous research while a total of 13 factors were added, these factors were obtained based on the Resource-based theory of the firm and other related literatures, were reviewed and used as a guide in obtaining these factors.

AI capability factors such as *Data, Artificial intelligence capability, Knowledge sharing, Organization Cohesion, Technology, organization creativity, Basic Resources, Technical Skills, Business Skills, Intangible Resources, Tangible Resources, interdepartmental Coordination, Risk proclivity, Organizational change capacity, Collaboration, Human Resources, organization performance and organization success* were combined using flow arrows to show the casual relationship of one factor to the other, which resulted in a more robust Conceptual AI capability model. These factors play a key role in deciding the success of an organization. The use of AI technologies enhances efficiency and innovation, while collaboration ensures a synergistic environment that gives room for creativity and problem-solving. The organization's structure sets the foundation for effective coordination, ensuring resources are in accordance with strategic objective. Furthermore, resources, such as a skilled and motivated workforce, contribute to the organization's adaptability and resilience. Also, tangible resources such as physical assets and financial capital, provide required support for operational excellence and growth. Therefore, a good and harmonious combination of these factors, will propel organizations towards a lasting success in a dynamic business environment.

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